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Non-Invasive RF Sensing for Detecting Breathing Abnormalities using Software Defined Radios

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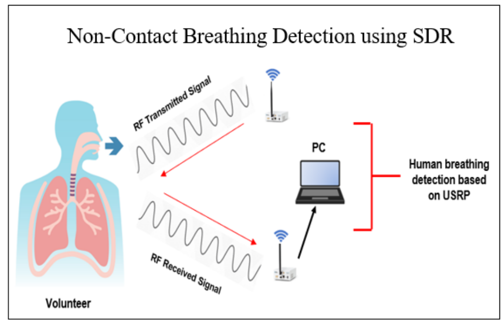

***Abstract*— The non-contact continuous monitoring of biomarkers comprising breathing detection and heart rate are essential vital signs to evaluate the general physical health of a patient. As compared to existing methods that need dedicated equipment (such as wearable sensors), the radio frequency (RF) signals can be synthesised to continuously monitor breathing rate in a contact-less setting. In this paper, we proposed the contact less breathing rate detection using universal software radio peripheral (USRP) platform without any wearable sensor. Our system leverage on the channel state information (CSI) to record the minute movement caused by breathing over orthogonal frequency division multiplexing (OFDM) in multiple sub-carriers. We presented a comparison of our breathing rate detection with wearable sensor (ground truth) results for single human subject. In this paper, we used wireless data to train, validate and test different machine learning (ML) algorithms to classify USRP data into normal, shallow and elevated breathing depending on the breathing rate. Although different ML models were developed using the K-Nearest Neighbor (KNN), Discriminant Analysis (DA), Naive Bayes (NB) and Decision Tree (DT) algorithms, however results showed KNN based model provided the highest accuracy for our data (91%) each time the trial was made. DT (17.131%), DA (59.72%) and NB (48.99%). Results presented in this paper showed that USRP based breathing rate is comparable to the wearable sensor demonstrating the potential application of our method to accurately monitor breathing rate of patients in primary or acute setting.**

***Index Terms*— Vital Signs, university software radio peripherals USRPs, channel state information, software defined radios, healthcare application.**

I. Introduction

THERE is a growing interest in the development of universal, contact-less and wireless sensing technologies to monitor daily activities. Several approaches for tracking human health and vital signs including breathing detection have been developed recently. Some of them include the use of smartphones and wearable sensor [1], [2], doppler radar [3], [4], Wi-Fi [5], ultra-wideband radar [6] and frequency modulated carriers [7]. Traditional techniques such as the received signal strength (RSS) provide a single frequency carrier power measurement with regards to full available frequency bandwidth. Amongst other traditional ways methods to monitor vital signs include wearable sensors, accelerometers (e.g. smartphones) or imaging sensors [8], [9]. Wearable sensor and accelerometers require physical contact with the body and have particularly slow response time whereas the imaging sensors are parasitical of particularity [10] and have issues to penetrate through walls, and darkness [11]. Radio frequency (RF) based systems offer non-invasive breathing rate monitoring through analysis of RF signal reflected off the human body. RF based monitoring systems which use frequency modulated continuous wave radar [12], [13] or doppler radar [4] are complex and expensive. Breath-tracking using RSS wireless devices are discussed in [15], have limited bandwidth around 7 Ghz and 60 Ghz millimetre wave signal which leads to false detection in long distance and require high gain directional antenna to covered. Mechanisms such as the USRP, frequency-modulated continuous-wave (FMCW), radar sensor and passive radar sensor [12], [13], [14] offer low-cost, long-term non-invasive breathing rate monitoring without requiring hospital visits or a physical contact. However, these systems need dedicated software and hardware setup operated at higher frequency range.

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Recent work by *Patwari et al.* [15] and *Kaltiokallio et al.* [16] used RSS and CSI data obtained using Wi-Fi signals to detect human breathing. This approach requires extra wireless sensor nodes to be deployed in indoor settings. Another study by *Nasser, et al.* [17] utilised WiFi RSS for breathing rate estimation and is capable of monitoring breathing for multiple people in parallel. Channel state information (CSI) is temporally more stable as compared to RSS as it presents both amplitude information and phase information. Recently, *Wang, et al.* [18] exploited CSI phase differences from the Wi-Fi router. The channel state information based wireless sensing systems have been also used for detecting respiration rate of people. For example, the author in [19] shown breathing detection based on CSI that extracted from WiFi. The achieved accuracy of this system reaches 94%. Moreover, the work shown in [21] use the CSI amplitude information to measure respirator rate when the person is asleep, this system requires the person to remain asleep. CSI based detection systems have numerous advantages; they do not require any wearable devices and also preserve user privacy. Although, the CSI-based method is efficient for activity detection in indoor settings, the main limitation of using Wi-Fi routers is their scalability, flexibility, and under-reporting of subcarriers. Network interface card (NIC) used by CSI systems only exploit 30 subcarriers and not revealing all 56 frequency channels transmitted by Wi-Fi router which accounts for 42% of loss in frequency carriers. Also, NIC based systems do not have the flexibility to increase/decrease frequency subcarriers, power level of transmitter signal, remove noise, and change operating frequency [22], [20].

By extracting the CSI data using USRPs transceiver model, our system allows custom configuration transmitted and received power and the operating frequency swing. In addition, it offers easy implementation of signal processing algorithms and the ability to reuse hardware (e.g. self-designed antennas). In this paper, we propose a flexible and scalable wireless sensing driven by USRP in conjunction with machine learning algorithm to detect human breathing. Our system designed using a MATLAB Simulink model, exploits 64 OFDM subcarriers to receive all the transmitted sub-carriers and detect breathing rate of single person. Thy system we have proposed overcomes all these challenges as USRP operating frequency is flexible, number of subcarriers can be changed in real time with low-noise figure. We have used USRP by transmitting and receiving N number of multiple OFDM subcarriers as compared to the counterpart where only limited numbers are available. Our algorithms provide real-time classification on the collected data from human breathing activities and high-classification accuracy for empirical results. The results obtained using USRP based wireless sensing for activities of respiration are highly accurate as compared to off-the-shelf wireless devices each time when activities and experiments are performed. Our system can also be used to detect large scale body movements of a person.

In the rest of this paper, we explain the design of SDR based human activity detection platform and signal propagation. We describe the experimental setup and system parameter and evaluate the performance of the system followed by the conclusion.

A. Contribution and Novelty

Numerous studies have demonstrated CSI based on Wi-Fi signal to recognise human movement exploiting lowcost small wireless devices such as Wi-Fi router, network interface card [20][22]. The main limitation of using these devices is the scalability, flexibility, and under-reporting all group of subcarriers. The Wi-Fi sensing for human activity recognition only report limited number of sbucarriers. The software defined radio allows us to change various parameters such as number of frequency carriers, power level and radiation pattern in real-time. In addition, systems based on SDR are also flexible, scalable and delivers desired result reliably and accurately.

II. METHOD

In this part, we discussed the design of simulink project and generating RF signal through the USRP.

A. System Overview

In the transmitter operation, we designed a MATLAB Simulink program to generate the OFDM signal for transmitter and receiver process over multiple subcarriers based on universal software radio peripheral USRPX300. Random data bits were generated from work space with probability of 0.75. then QPSK modulation scheme were carried out to convert these bits to symbols, each two bits represent one symbol. Then the symbols were connected to single subcarrier are plugged into the converter to transform it serial to parallel to by applying Inverse Fast Fourier Transform (IFFT) operation and transfer the symbols from frequency domain to time domain. After that a cyclic prefix are then given into the system between each symbol to mitigate the effect of co-channel interference of the collected signal at the receiver side. Then the received signal is up-converted through Digital-to-Analog converter (DAC) using USRP platform.

At the receiver end, the OFDM signal was collected by the received antenna that equipped on the second USRPX310, then the USRP convert the OFDM signal from analogue to digital and next down converting it to the original base band signal, Afterwards a low-pass filter was used in the USRP to generate the I/Q base-band wave form and remove the effect of high frequencies. Besides, OFDM bits are normally sorted into frames so that the received signal needs to be synchronised in time and frequency to obtain the start of the OFDM symbol and then Fast Fourier Transform (FFT) algorithm used to convert the based-band signal from time to frequency domain. Also, the guard interval removed through retrieving the original signal. The block diagram of the transceiver operation can be shown in figures 1.

B. Signal Model

The proposed system used CSI signal for the transmitter and receiver operation. The CSI represent the channel frequency response (CFR) for each OFDM subcarrier includes amplitude

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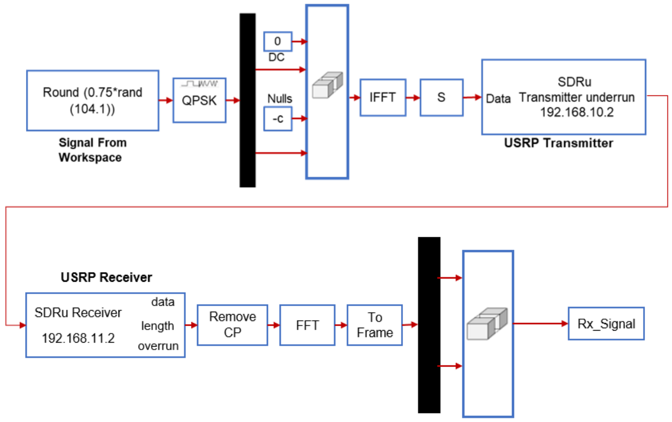

Fig. 1. Simplified OFDM Simulink Model for Transceiver Operation.

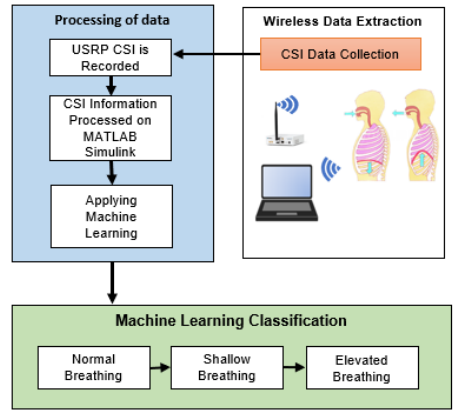

Fig. 2. Flowchart of the proposed System for collecting channel state information using USRPs.

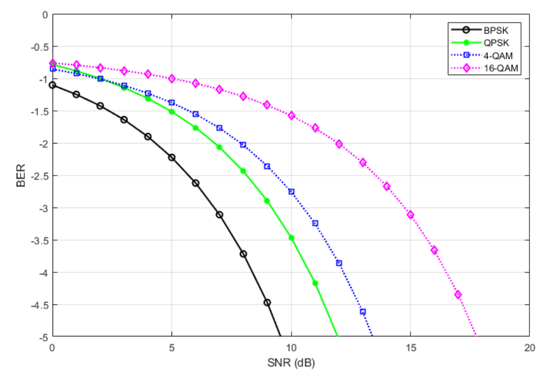

Fig. 3. Simulated Bit error rate analysis of OFDM system.

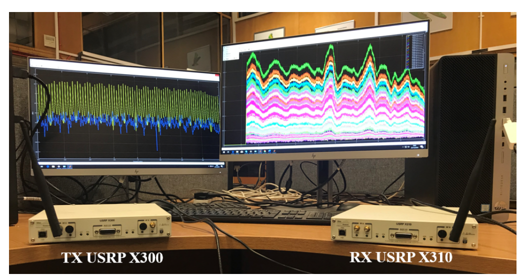

Fig. 4. Hardware design of System Setup .

information and phase information. This system has been developed and implemented only to extract the wireless channel state information amplitude response for human activities. The CSI phase information is inapplicable due to presence of random noise, that is why it was not considered. Equation (1) presented the received CSI signal.

$$H\left(f_i\right) = H\left(f_i\right) e^{j\angle H\left(f_i\right)} \quad (1)$$

In this expression, H(f_i) describes the information of amplitude and $\angle$ H(f_i) explains the phase information for CSI signal. The measured OFDM subcarriers contain the values of CSI packets and it can be shown in equation (2). [23].

$$\mathrm{H} = \left(h_1, h_2, h_3, \ldots\ldots., h_N\right) \quad (2)$$

In this system, IFFT and FFT blocks measure the response of amplitude and phase. By performing IFFT at transmitter side and FFT at receiver side. The channel response can be expressed as following. [24].

$$H(f) = \frac{x(f)}{Y(f)} \quad (3)$$

Where X(f) refers to the response of the OFDM transmitted signal, H(f) describe the system channel response and Y(f) represent the response of the OFDM received signal.

C. Collection of data

The collection of three breathing events carried out in lab environment using single subject. The experiment consists of two USRPs X300/310 and the distance between the subject and USRPs antenna keep it as 0.4 meters. The volunteer started breathing normal, Shallow, and heavy and the reflected signal from human body once performing breathing activities is stored as wireless channel state information WCSI data.

D. Data extraction

At the receiver side. The OFDM signal utilized for fine grained wireless channel state information extraction then the amplitude frequency response for each breathing activity will be observed constantly for 10 seconds. And each collected signal consists several OFDM samples and subcarriers. Time and samples can be represented as the received number of samples in a unit time.

The obtained data from CSI is in the row form and needs processing to provide meaningful information using three following steps.

I- Cleaning the data by eliminating the terrible CSI data.

II- Applying low pass filter for removing the noise.

III- The grouping technique is performed to detect the correlation between the CSI values.

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E. Additive White Gaussian Noise

The Additive white Gaussian noise channel (AWGN) was considered for simulated result. This wireless medium model has been widely exploited in identifying the most feasible modulation scheme. The main advantages of this wireless channel model is it's least complexity in terms of test and deployment and represents the real man-made noise with regards to other multi-user interference [25].

F. Bit Error Rate of the USRP Model

Bit error rate (BER) gives the number of bits in error per unit time and the most important parameters to analyse the performance of any robust, efficient and accurate wireless medium system. Figure 3 shows BER versus SNR (Eb/No in dB) performance analysis of various modulation techniques. The additive white gaussian noise wireless channel was used to obtain simulated results. It is clear from the figure that BPSK has lower BER than QPSK and QAM. For instance, at SNR 10 BER for BPSK is 0 but for QPSK and 16 QAM is greater than 10^{-4}. Also, at SNR 14 BER for QPSK is 0 whereas for 16 QAM is approximate 10^{-3}. Therefore, Quadrature amplitude modulation (16-QAM) has greater Bit Error Rate (BER) as compared with lower order Binary Phase Shfit Keying (BPSK). This is also proven for our proposed model as well.

G. Feature extraction

CSI information represent fine-grained data and feature extraction is used for transferring the CSI data into meaningful information. Several feature in the time domain are implemented. (1) the normalized standard division indicate the dispersion degree among sampling points of the CSI signal. (2) the root mean square (RMS) is used to calculate the magnitude of CSI information. (3) peak to peak value is used to calculate the differences between the maximum and minimum amplitudes values of the collected CSI signal. (4) the peak factor indicates if there is influence on the CSI information. (5) waveform factor is used to represent the ratio of the root mean squire value to the average value. (6) FFT is used to excerpt the frequency component with peak to peak values of the signal. (7) spectrum probability and signal energy are unique and essential for extraction of frequency domain analysis.

III. EVALUATION

Our experiments were carried out to test human vital signs monitor the respiratory rates and identify anomalies. This section describes the hardware and software setup involves the parameters used in the designed system.

A. Experimental method

The experiment is performed in lab environment using two NI USRPX300/310 platforms that have been built for real time data acquisition. The USRPs is fitted with two omni directional antennas for the transmit and receive operation. The antenna has frequency range from 2.4 GHz to 5.9 GHz. The key advantage of using omni-directional antenna is that it can detect human activities in LOS and NLOS. Besides, directional antennas, yagi antennas have also been tested on our system and provided similar results.the experiment was conducted at 5.32 GHz,With the increase in frequency, the range resolution increases and vice versa. The respiratory rate will be best detected when the USRP transceiver model is tuned at higher frequencies. However, the distance in terms of monitoring person will be decreases and signal will be highly susceptible to external noise. Furthermore, two PCs was used to implement the trial and a 1 GB Ethernet cable was used to transmit the data to the centralize personal computer to process the acquired USRP data and classify normal respiratory rate against abnormal breathing rate. The trial were processed using MATLAB SIMULINK software. For the demonstration, the experiment carried out in lab environment, which was a large room with office environment. Also, the volunteer was positioned 0.4 m away from the antenna, in order to achieve optimum performance. The experiment was undertaken to capture the changes occurred in CSI data due to chest movement cause by respiratory patterns. Also, we used wearable sensor (Ground truth) to ensure that the collected data from USRP is working properly.The breathing sensor used as a reference was SA9311M – manufactured by Though Tech. The reference wearable sensor is a highly sensitive to chest movements and abdominal expansion/contraction and outputs the respiration waveform. Finally, four algorithms such as KNN, DA, NB and DT were applied to process and classify the collected data. In the same scenario, we have performed experimental campaign ask the volunteers to perform normal breathing, shallow breathing, and elevated breathing while they were under test. the experimental setup is shown in figure 4.

TABLE I
SOFTWARE CONFIGURATION AND PARAMETERS SELECTION

Parameters	Values
Input random bits	round(0.75*rand(104,1))
Sample time rate	132/104*(1/132e4)
Modulation type	QPSK
Bit per symbol M	2 bits
Used Subcarrier	64 subcarriers
Used Null subcarrier	12
Used Pilot subcarrier	4
Samples per frame	Used subcarrier log2 (M)
NFFTpoints	64,128,256,512,1024 and 2048
Cycle prefix	NFFT-data subcarrier

B. System Parameters Selection

In this part, we introduce the system parameters selected for software and hardware system setup. Firstly, Simulink model was implemented in MATLAB based on QPSK modulation scheme and OFDM signal. The parameters values used in our software as shown in Table I. We tested the hardware parameters by running QPSK transmitter and receiver examples on MATLAB, then we applied our own hardware parameters of the USRPs X300/310 to capture the wireless CSI of small body movement. The trial was conducted at 5.32 GHz for USRP platform and the sample rate chosen in this experiment was 80. Configuration for the hardware parameters is shown in Table II.

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TABLE II
HARDWARE CONFIGURATION AND PARAMETERS SELECTION

Platform	USRP X300/310
TX serial number	192.168.10.1
RX serial number	192.168.11.1
Channel mapping	1, 2
Gain (dB)	70
Master clock rate	120 Mhz
Centre frequency of USRP	5.32Ghz
Sample time rate	1/80e4
Local oscillator offset	Dialog
Interpolation factor	500
PPS source	Internal
Decimation factor	500
Clock source	Internal
Transport data type	Int16

IV. RESULTS AND DISCUSSIONS

In this section, we evaluated the overall performance of the breathing rate under three different regimes; normal breathing, shallow breathing, and elevated breathing. The three breathing regimes were measured by two devices USRPs and wearable sensor (ground-truth) after acquiring ethical approvals from University of Glasgow. Firstly, the volunteer was asked to breath normally followed by shallow breathing and the elevated breathing for 10 seconds each. We collected the data from sensor and the USRP simultaneously. The wearable sensor was attached to the participant body's chest. While testing our experiment and recording of the data, multiple factors were considered in real-time environment such as the physical objects that could affect the wireless received signal. First, we tested our system with QPSK transmitter and receiver examples with USRP to ensuring that there is no error acquired for the device configuration and whether working properly. Then we used our own Simulink model to captivate the wireless signal for small scale body movement of the human. The number of packets characterise the number of subcarriers of the OFDM signal. Figure 5 shows Wireless channel state information (WCSI) waveform of normal breathing for both USRP and wearable sensor.We have used The Breathing Rate Belt and Pressure Sensor 'product code 3190 as reference sensor. The human started sitting in front of the USRP and kept the distance as 0.4 meters. Also covered the sensor around his body and started breathing normally and recorded the data of both the USRP and sensor. We noticed that the amplitude changes were normally based on the habitual breathing of the human. In this case, the practice was repeated several times with same amplitude differences detected.

During recording of the wireless data from human respiration, we set the time to 10 seconds. Transmitted packets were 10000 and received 8642 out of 10000 packets for 10 second time duration. We repeated the normal breathing activity 10 times and received same number of packets of each activity performed. We used the wearable sensor as reference. As the measured data of wearable sensor are reliable and presents the ground truth of the breathing detection. The wireless value is close to the wearable value. This ensures that the system can measure the human breathing without wearing any sensor and it can be alternative of wearable devices. Figure 6. shows the results when of shallow breathing. The figure illustrates the prominent changes in the amplitude. The time duration in this practice was also set for 10 seconds including the same number of send and received packets of the previous activity of normal breath. In this work, we have used software-defined-radio model University Software Radio Peripherals (USRP) by transmitting and receiving N number of multiple OFDM subcarriers as compared to its counterpart where limited numbers are available. In our experiment, The Orthogonal Frequency Division Multiplexing (OFDM) with 64-subcarriers is used to extract the Wireless Channel State Information of breathing activities.

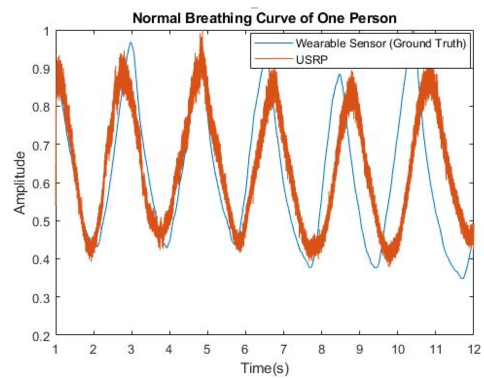

Fig. 5. WCSI during Normal Breathing for USRP and Sensor.

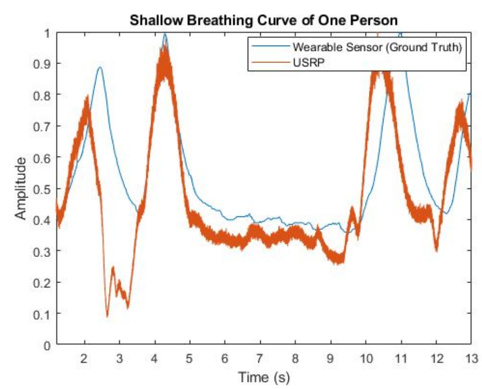

Fig. 6. WCSI during shallow Breathing for USRP and Sensor.

Figure 7 represents the results of the elevated breathing. It can be seen that the signal increased in the cycle of the amplitude compared to the waveform of normal breathing. Also, comprised the similar number of the transmitted and received packets for 10 seconds time duration. Besides, the referenced signal is reliable and has less noise compared with the signal obtained from the SDR or is effected by any physical factors as a result of performing the breathing activities.

A. Machine Learning Classification

This section provided details on the discussion of four different machine learning algorithms used to classify three breathing events and evaluate the suggested system based on percentage accuracy. The dataset performance was obtained

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TABLE III
FEATURE EXTRACTION EQUATIONS FOR DATA CLASSIFICATION

NO	Feature	Expression
1	normalized standard division	$Y_{sd}=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - y_m)^2}$
2	the root mean square (RMS)	$Y_{RMS}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$
3	Peak to peak value	$Y_{ppv}=Y_{max} - Y_{min}$ $(i=1,2...,N)$
4	Peak factor	$Y_P=\frac{max(x_i)}{Y_{RMS}}$ $(i=1,2...,N)$
5	Waveform factor	$Y_w=\frac{N*Y_{RMS}}{\sum_{i=1}^{N}X_i}$ $(i=1,2...,N)$
6	FFT	$Y_{FFT}=\sum_{n=-N}^{N}x(n)e^{-j\frac{2\pi}{N}nd}$
7	Spectrum probability	$Y_{SE}=\sum_{n=-N}^{N}p(d)^2$
8	Signal energy	$Y_M=\sum_{n=-N}^{N}p(d)\ln p(d)$

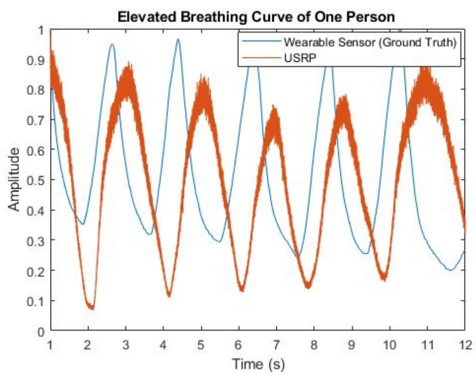
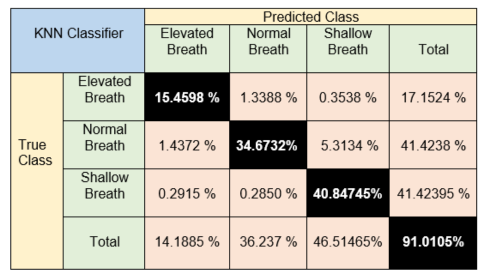


Fig. 7. WCSI during elevated breathing for USRP and Sensor.



KNN Classifier		Predicted Class: Elevated Breath	Normal Breath	Shallow Breath	Total
True Class	Elevated Breath	15.4598 %	1.3388 %	0.3538 %	17.1524 %
	Normal Breath	1.4372 %	34.6732%	5.3134 %	41.4238 %
	Shallow Breath	0.2915 %	0.2850 %	40.84745%	41.42395 %
	Total	14.1885 %	36.237 %	46.51465%	91.0105%

Fig. 8. Confusion matrix for KNN classifier.

TABLE IV
FOLLOWING PARAMETERS WERE USED FOR KNN AND DT CLASSIFIER

Classification Algorithm	Parameters	Setup
Decision Tree	Maximum number of dataset splits. Split Criterion	4 Gini's diversity index
K–Nearest Neighbour	Number of Neighbours. Distance Metric	2 Euclidean

using different ML techniques as listed above. A 10-fold cross validation technique was used on the USRP data containing different respiratory patterns.

The accuracy is calculated as an average of the 10 sets of testing data used in each of the 10 cross fold validation process. The below Figures 8-9 shows the confusion matrix of KNN and DT algorithms. It can be seen from Confusion matrix in figure 8-9 that the y axis represents the predicted classes and x axis symbolizes the true class of the algorithm.

The machine learning algorithms were run using the following parameters. KNN is configured using 3 K-samples using the Euclidean distance. Discriminant Analysis DA was configured as linear. Naive Bayes NB used the normal distribution method. DT algorithm is set up to use 50 splits in the decision tree.

The KNN classifier provide the best classification accuracy among other algorithms. The value for KNN algorithms was selected as 3. The confusion matrix in figure 8 represent a total of 1075851 samples were received over a period for all breathing events. For a combined activity of elevated breath, 15.4598% were correctly classified as elevated breath. While 1.3388% samples were incorrectly classified as breath normal and 0.3538% samples as shallow breath activity. Almost similar number of samples were correctly identified as breath normal and 1.4372% samples were determined as elevated breath besides 5.3134% CSI samples as shallow breath. 40.84745% samples were predicted as shallow breath while a combine of nearly 0.5765% were unclassified as other remaining activities. The overall percentage accuracy using KNN classifier was obtained as 91.0105%

DT algorithm performed worse, providing overall accuracy of only 71.131%. It can be seen in Figure 9 that for first activity, there were 5.7335% classified correctly. 4.5800% CSI samples were identified as breath normal activity (false negative) and 6.8390% samples as shallow breathing. The classification of normal breathing samples slightly more accurate. 1.4247% and 14.7483% samples were classified incorrectly as elevated breath and shallow breath, this leaves the remaining 25.2507% breath normal samples as being correctly classified.

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DT Classifier		Predicted Class: Elevated Breath	Normal Breath	Shallow Breath	Total
True Class	Elevated Breath	**5.7335 %**	4.5800 %	6.8390 %	13.1525 %
	Normal Breath	1.4247 %	**25.2507 %**	14.7483 %	41.4237 %
	Shallow Breath	0.3909 %	0.8858 %	**40.1471 %**	41.4238 %
	Total	7.5491 %	30.7165 %	61.7344 %	**71.1313%**

Fig. 9. Confusion matrix for DT classifier.

For the shallow breath activities, 40.1471% samples were classified correctly, then 0.3909% and 0.8858% samples were misclassified. The other algorithms tested were discriminant analysis (DA) and native bayes (NB) which produced poor results compared to KNN and DT algorithms with accuracy of only 59.72% for DA and 48.99% for NB. Table V shows the accuracy comparison for all used classifiers.

TABLE V
PERCENTAGE ACCURACIES OF EACH CLASSIFIER

Classifier models	Classification Accuracy %
Nearest Neighbor (KNN)	91.0105
Decision Tree (DT)	71.131
Discriminant Analysis (DA)	59.72
Naive Bayes (NB)	48.99

V. CONCLUSION

In this paper, we presented tracking breathing rate detection based on wireless signals. In particular, we designed a MATLAB Simulink model based on universal software radio peripheral (USRP) to capture small scale body movement. Our algorithms grounded on channel state information (CSI) information in time domain can detect the breathing rate for individual non invasively. In this work, we studied three breathing scenarios; normal , shallow and elevated breathing. We compared our results with a data harvesting sensor as the ground truth. Our results show high correlation between the two methods. Machine learning algorithm were applied for processing and classifying the data to provide excellent performance and robustness on breathing rate. For future work, we will increase complexity of the data collection by monitoring multiple people simultaneously, increase other movements in the surrounding and so on. our aim is to make this system more generalize, acquiring data in elderly care centre or hospitals in different geometrical settings. The CSI at heterogenous environment varies also, we will develop an algorithm for calibration in future work that in independent of geometrical structure.

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